INVESTIGATION OF THE UTILITY OF THE VEGETATION CONDITION INDEX (VCI) AS AN INDICATOR OF DROUGHT

A Thesis

by

SRINIVASAN GANESH

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

December 2007

Major Subject: Geography

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Approved by:

Chair of Committee,	Steven Quiring
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ABSTRACT

Investigation of the Utility of the Vegetation Condition Index (VCI) as an Indicator of Drought. (December 2007)

Srinivasan Ganesh, B.Tech., Indian Institute of Technology, Bombay

Chair of Advisory Committee: Dr. Steven Quiring

The relationship between the satellite-based Vegetation Condition Index (VCI) and frequently used agricultural drought indices like Palmer Drought Severity Index, Palmer's Z-index, Standard Precipitation Index, percent normal and deciles was evaluated using a comparative correlation analysis. These indices were compared at the county level for all 254 Texas counties for the growing-season months (March to August) using monthly data from 1982-1999. The evaluation revealed that the VCI was most strongly correlated with the 6-month SPI and the PDSI. This suggests that the VCI is most similar to drought indices that account for antecedent moisture conditions. There was also significant spatial variability in the magnitude of the correlations between the VCI and the drought indices. The reasons for this variability were explored by utilizing additional data such as irrigation, prevalent landuse/landcover, water table depth, soil moisture levels and soil hydrologic/hydraulic properties. The results demonstrated that mean annual precipitation, soil moisture, landuse/landcover, and depth of the water table accounted for a significant amount of the spatial variability (explaining more than 75% of the variance) in the relationship between the VCI and traditional drought indices.

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1. INTRODUCTION

1.1 Significance of Drought

Drought is a recurrent phenomenon that has a major impact on ecosystems, natural habitats, and agriculture. Drought is acknowledged as United States' costliest natural hazard causing, on average, US$6-8 billion in damages annually (Wilhite 2000). The major droughts of the 1930s and 1950s in the Great Plains and southwestern United States had severe environmental and social impacts causing great agricultural damage and population exodus and leaving behind exhausted soils and depressed local economies (Worster 1985). Unlike other natural hazards, like hurricanes, where destruction occurs over a short period of time, drought is a phenomenon which develops slowly over a long period of time. Drought also can affect vast areas, and it leaves behind lingering effects in its aftermath. The ten major droughts/heatwaves in the period 1980-2003 were responsible for almost 42% of the weather-related monetary losses which was more than the losses from hurricanes and tropical storms (28%) (Ross 2003). The economic and social impacts of drought are spread over a long period of time, thus making drought the worst of all natural hazards (Ross 2003).

1.2 Drought Defined

The wide variety of social and economic sectors affected by drought, its diverse spatial and temporal distribution, as well as different causes for the onset of drought have made it difficult to develop a single definition (or scale of measurement) for drought. The American Meteorological Society categorizes drought into four broad categories (Heim Jr. 2000): *meteorological or climatological drought* which pertains to the atmospheric

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This thesis follows the style of *Remote Sensing of Environment*.

conditions leading to the absence or reduction of precipitation over a length of time, *agricultural drought* which is the reduction of crop-yield due to below average precipitation, *hydrological drought* occurs when the decreased precipitation leads to reduced streamflow, groundwater supply and lake and reservoir levels, and *socioeconomic drought* caused by demand significantly greater than supply of some economic good (e.g., hydroelectric power) affected by the other three drought types defined above. The root cause of drought, for all four types, is a prolonged deficit of precipitation (Kogan 1998). In this study we adopt the remote sensing perspective taken by Tucker (1987) in which drought is defined as a period of reduced plant growth as compared to the historical average, caused by below normal precipitation.

1.3 Problem Statement

This study evaluates the ability of the satellite-based Vegetation Condition Index (VCI) to monitor and quantify meteorological/agricultural drought in Texas. It will compare the VCI to traditional station-based drought indices in a region routinely affected by drought. Additionally the study will investigate how local variables like landuse, soil properties and depth-to-water table influence the strength of the correlations between the VCI and traditional station-based indices. The methodology for identifying the onset and quantifying the severity of drought using satellite-based vegetation indices rests on the assumption that drought causes the photosynthetic capacity of vegetation to decrease and that this decrease can be observed and quantified by satellite sensors. This assumption is justified by previous studies that have demonstrated that there is a strong relationship between vegetation health (vigor), as measured by AVHRR (Advanced Very

High Resolution Radiometer) sensor (or many other optical satellites), and moisture conditions (Goward 2002; Nicholson 1994; Wang 2001).

1.4 Thesis Objectives

The main objective of this study is to investigate the suitability of the satellite-based Vegetation Condition Index (VCI) as an effective substitute for traditional station-based indices like the Palmer Drought Severity Index (PDSI) and the Standard Precipitation Index (SPI) for monitoring drought in the state of Texas. Specifically this study will:

1. Compare the performance of the satellite-based VCI with traditional station-based indices like the Palmer Drought Severity Index (PDSI) and the Standard Precipitation Index (SPI). In particular, this study will allow us to evaluate the accuracy of the VCI for determining the onset and severity of agricultural drought in Texas. Questions that are addressed are: What is the relationship between station-based drought indices and satellite-based drought indices? What are the strengths and weaknesses of both approaches (satellite versus station)? Where is it inappropriate to use satellite-based indices?

2. To investigate the spatial pattern observed in the correlation between the VCI and the ground-based indices by incorporating additional datasets such as soils, irrigated area and landuse/landcover data to determine which of these variables significantly influence the correlation.

1.5 Significance of the Research

Texas, with 22.5% of land under agriculture, ranks number two in the United States in terms of value of agricultural products sold and it ranks first in terms of the value of livestock, poultry and other products. Studies have shown that Texas is visited by serious drought at least once in a decade (Riggo 1987). The 1998 drought caused a monetary loss of $5.8 billion (Chenault 1998) to the state, which is about 39% of the annual agriculture revenue of the state. The damage caused by the major drought of the 1950s and the droughts of the 1980s and 1990s exposed the need to develop research tools to detect the early onset of drought and develop appropriate drought mitigation policies.

This research will evaluate a remote sensing-based approach for assessing, monitoring and managing drought at a relatively fine spatial (8 km) resolution. Such a remote-sensing-based model would provide the farming community, water managers and government agencies a high-resolution tool for assessing, monitoring and managing drought.

2. REVIEW OF DROUGHT INDICES

2.1 Drought Indices

Once the type of drought is defined, the magnitude and duration of the drought can be quantitatively expressed using a drought index. A drought index is a composite of various hydrological and meteorological parameters like rainfall, temperature and runoff. A drought index provides a standardized method for comparison of the moisture conditions between different regions or time periods by business and government agencies. Drought indices have been used as an early drought-onset warning system (Lohani 1997), to predict crop yield (Kogan 1998; Kumar 1997), to compare droughts in different regions (Alley 1985; Dai 2004; Kumar 1997), to determine the distribution of relief in drought-affected areas (Wilhite 1986), and in calculating the probability of drought termination (Karl 1987). Traditional station-based drought indices like the Palmer Drought Severity Index (PDSI and the associated Z-index) (Palmer 1965) and the Standard Precipitation Index (SPI) (McKee 1993) are used extensively for drought monitoring and forecasting. These indices described in the following section.

2.1.1 Palmer Drought Severity Index (PDSI) and the Z-index

The PDSI, introduced by Palmer (1965) is one of the most commonly used meteorological drought indices in the US (Heim Jr. 2000). The PDSI is calculated based on daily precipitation, daily temperature and the Available Water Holding Capacity (AWHC) of the soil. It is a standardized measure of moisture conditions, with an approximate range of -6 (extremely dry) to +6 (extremely wet). The PDSI is calculated using a two-layer, bucket-type soil moisture model. The PDSI assumes that runoff begins after both top and bottom layers are saturated. Evapotranspiration is assumed to take place at the potential evapotranspiration rate determined by the classic Thornthwaite model (Thornthwaite 1948) and reduction in soil moisture occurs when evapotranspiration exceeds precipitation.

The Z-index is an intermediate term in the PDSI, and it is a measure of the surface moisture anomaly for the current month in relation to the normal moisture conditions (determined from at least 30 years of data). The Z-index, Z_i is given by the product:

$$Z_i = d_i K_i \tag{1}$$

where d_i is the departure from the normal moisture for the current month, and K_i is the Climatic Characteristic (i.e., a weighing factor to adjust for the severity of the surplus (or deficit of moisture relative to the local climatic conditions). K_i is a function of location and time of the year as apparent from its constituent formula:

$$K_i = \frac{17.67}{\sum \overline{D_i} K} * K_i^{'} \tag{2}$$

where $\overline{D}_i$ is the mean of the absolute values for each month of the year.

The PDSI, for any given month i, denoted by X_i is given as:

$$X_i = (Z_i/3) + 0.897 * X_{i-1} \tag{3}$$

where the coefficients 1/3 and 0.897 are empirical constants known as Duration Factors which determine the duration that a particular spell will last.

As apparent from their formulae, both the Z-index and the PDSI utilize the same data, PDSI accounts for antecedent moisture conditions while the Z-index only uses conditions for the current month.

Thus, the Z-index is a better measure of agricultural drought because it responds to short-term (e.g., monthly) fluctuations in soil moisture (Karl 1986). PDSI and the Z-index are calculated using both temperature and precipitation and as much as 30% of PDSI's variation is due to air temperature (Dai 2004).

2.1.2 Standard Precipitation Index (SPI)

The SPI was introduced by McKee (1993) to measure the precipitation anomalies over different time scales so as to account for the impact of drought on the availability of soil moisture, groundwater and reservoir flow. For a given location, the historic precipitation record is obtained and fitted to a probability distribution and transformed into a Gaussian distribution in order to make the mean SPI at that location zero. For any of the time scales, a period is defined as a drought if the SPI is continuously negative and falls below -1 (McKee 1993) indicating a moderately dry period. The end of the drought is marked by the SPI values becoming positive. Summation of the SPI values within this time period yields the intensity of drought.

A number of studies (Gutman 1999; Kogan 1998; Kumar 1997) have found that the Pearson III distribution is the most well-suited for calculating the SPI, and it was adopted in this study.

2.2 Limitations of Traditional Drought Indices for Monitoring Drought

The spatial resolution of traditional drought indices depends on the density of the distribution of meteorological stations. Also, meteorological stations can suffer from incomplete data acquisition (missing data) and most meteorological stations do not provide data in real time.

The data collected by the meteorological stations are location-specific. Thus it may not adequately reflect the true spatial variability of the phenomenon being measured (in this case, drought). The resultant indices computed using station-based data suffer from the above generic limitations. In addition, there are a number of index-specific limitations that are discussed in the following sections.

2.2.1 Limitations of the PDSI

Though very widely used, the PDSI has a number of limitations that are described below. Potential evapotranspiration (ET) is calculated in the PDSI using Thornthwaite's method (Alley 1984). Jensen (1990) studied various methods of estimating ET under a variety of climatic conditions and determined that the Thornthwaite equation was the most poorly performing method.

Palmer (1965) used a two-layer lumped parameter model that assumes a single water holding capacity for the top two layers regardless of the size of the area. For example, the soils in a climatic division (7000 to 100,000 km^2) are represented by a single parameter. The PDSI model fails to incorporate variation of soil properties which occur at a much smaller scale (Narsimhan 2004).

Studies have shown that the PDSI is not a good measure of agricultural drought, although it does correlate well with soil moisture content during the warm season (Alley 1985; Dai 2004). Since the PDSI is based on a water balance model, it is more suited to be a measure of hydrological drought (Alley 1985; Dai 2004). Also, PDSI does not take into account the influence of soil type, landuse and management practices in computing runoff.

2.2.2 Limitations of the SPI

The SPI also suffers from a number of limitations. The SPI does not account for soil properties, landuse and temperature deviations that are critical in influencing agricultural drought (Narsimhan 2004). Also, vegetation utilizes the available soil moisture at the root level rather than the entire precipitation. Hence, a soil-moisture-based drought index is more appropriate. Bhuiyan (2006)has also shown that external factors like aquifer-based water supply can cause areas of disagreement between vegetative drought and SPI-classified drought. SPI is calculated only using precipitation and so it does not take into account the atmospheric demand (PET) for moisture.

2.3 Satellite-based Vegetation Indices

Satellite-based indices offer significant advantages over traditional station-based indices because satellite-based indices provide a consistent spatial coverage and higher spatial resolution. Satellites provide regional coverage over wide scales and are thus able to capture the spatial variability of the phenomenon under observation providing information on a real-time basis. The two most widely used satellite-based vegetation indices are the NDVI and the VCI and they are described in the following sections.

2.3.1 Normalized Difference Vegetation Index (NDVI)

The Advanced Very High Resolution Radiometer (AVHRR) instrument is borne on board the NOAA series of Polar-orbiting Operational Environmental Satellites (POES). The AVHRR is a five channel passive scanning radiometer that is sensitive to light in the visible (channel 1 = 0.58-0.68 μm), near-infrared (channel 2 = 0.75-1.0 μm), mid-infrared (channel 3A = 1.58-1.64 μm, channel 3B = 3.55-3.93 μm), and thermal infrared (channel 4 = 10.3-11.3 μm, channel 5 = 11.5-12.5 μm) regions of the spectrum. The NDVI is based on the difference between maximum absorption in the red spectral region and maximum reflectance in the near infrared spectral region and is calculated using only channel 1 (visible – red) and channel 2 (near-infrared radiation (NIR)) as shown in Equation (4).

$$NDVI = \frac{(CH1 - CH2)}{(CH1 + CH2)} \quad (4)$$

Green and healthy vegetation show large NDVI values while rock and bare soil have nearly similar reflectance in the visible and near-infrared (NIR) ranges and thus have an NDVI index close to zero. Clouds, water and snow, however, have greater reflectance in the visible than the NIR and hence yield negative NDVI values. Thus NDVI has become an important tool for mapping changes in vegetation cover and gauging the impact of environmental phenomena such as drought and plant disease (Ichii 2002; Leprieur 2000).

Satellite-based vegetation indices (especially NDVI-based indices) have frequently been used to study drought (Anyamba 2001; Kogan 1990, 1995, 1998). Gutman (1990) successfully compared mid-afternoon surface temperatures and inter-annual differences in mean monthly NDVI with corresponding differences in the Palmer Drought Severity Index (PDSI). Anyamba (2001) used the departure of NDVI from its long-term average for a particular month, as an indicator of drought conditions in Africa.

However, a limitation of the NDVI in drought monitoring is the temporal lag between the rainfall event (or deficit) and its manifestation in the vegetation health and the consequent change in the NDVI values (Wang 2001). This has been addressed to some extent in recent studies. Yingxin (2007) conducted a five-year history investigation of MODIS NDVI and NDWI (Normalized Difference Water Index), an index computed using near infrared and short wave infrared which tracks the water content and concluded that the NDWI was more sensitive than the NDVI to the onset of drought and drought magnitude and also responded more quickly in a homogeneous grassland land cover study area.

2.3.2 Vegetation Condition Index (VCI)

Description

The Vegetation Condition Index (VCI), a pixel-wise normalization of NDVI over some time period, was developed by Kogan (1990; 1995) to make a relative assessment of changes in the NDVI signal by filtering out the contribution of local geographic resources to the spatial variability of NDVI. The VCI is computed as:

$$VCI_i = 100 * (NDVI_i - NDVI_{\min}) / (NDVI_{\max} - NDVI_{\min}) \tag{5}$$

where $NDVI_i$ is the smoothed weekly NDVI, $NDVI_{max}$, and $NDVI_{min}$ are maximum and minimum NDVI, respectively, for that pixel and 10-day period from multiyear smoothed NDVI data and *i* defines the 10-day interval. NOAA-AVHRR derived NDVI and its alterations (e.g., Standardized NDVI, NDVI anomaly) have been used in a number of studies to monitor areas prone to drought at regional and local scales (Bayarjargal 2006; Nicholson 1994). NDVI has also been shown to be an effective indicator of vegetation response to drought in the Great Plains of the USA (Ji 2003). However NDVI cannot take into account differences due to the productivity of the local ecosystem in order to determine vegetation health. For example, low NDVI values are expected in arid regions, while tropical rainforests show high NDVI values, even in relatively dry seasons. These NDVI differences represent the difference in local ecosystem resources and not the weather. This defect is addressed by the VCI. The VCI is an indicator of the relative healthiness (vigor) of the vegetation in response to weather with respect to the ecologically defined minimum and maximum limits. The VCI reduces noise in AVHRR data and increases the vegetation-response signal.

Studies Using the VCI

A study in Africa involving the use of VCI to model crop yield and detect the early onset of drought demonstrated that the spatial and temporal characteristics of drought can be monitored by use of the VCI (Kogan 1998). Gitelson (1998) used VCI-derived-vegetation density data to quantitatively assess vegetation state and productivity over large regions. The VCI was demonstrated to be an accurate assessor of unfavorable vegetation conditions particularly related to drought. Dabrowska-Zielinska (2002) used a combination of VCI and thermal indices to predict crop yield and identify critical growing periods in the crop cycle in Poland. Bhuiyan (2006) used the VCI to delineate vegetative drought zones in the Aravalli region (India) where the traditional SPI failed to detect drought due to interference of aquifer-based groundwater. Wan (2004) used a combination of VCI and thermal indices in the southern Great Plains of US to develop a near-real time drought-monitoring approach called Vegetation Temperature Condition Index (VTCI). This comprehensive approach was successfully validated using in situ precipitation data.

Limitations of the VCI

Some studies have shown that the VCI alone is not a reliable tool for the monitoring of drought. Singh (2004) in a study region in Uttar Pradesh, India found that the VCI showed depressed (lower than expected) values in wet months following a drought because the sudden increase in precipitation damaged crops and flooded agricultural fields. Thus, even though the ground was very wet, the vegetation was stressed. In such a case, the VCI mistakenly indicates that a drought is occurring. Bayarjargal (2006) compared satellite-based vegetation indices and traditional station-based drought indices and found that there was no agreement regarding the spatial extent of the drought among the two. The study also points out that it is difficult to identify the most reliable drought index because of the low spatial density of ground-based meteorological stations. Vicente-Serrano (2007) reported that VCI correlation with traditional drought indices like SPI varied with landcover type and the highest correlations were found in locations where the primary land-use was non-irrigated agriculture. Vicente-Serrano (2007) also reported that correlations between the VCI and traditional station-based drought indices decreased during extremely wet periods since vegetation cannot use all of the precipitation (i.e. they have an upper limit), while the traditional drought indices do not have an upper limit. The study also reports that the type of the vegetation affects the correlation. For example, deep-rooted forests can tap into groundwater and thereby mitigate the effect of drought conditions.

3. METHODOLOGY

3.1 Study Area

The state of Texas has an area of 678,051 km² and extends from latitude 25° 50' N to 36° 30' N and from longitude 93° 31' W to 106° 38' W. Texas has 10 climatic regions, 14 soil regions, and 11 distinct ecological regions. It is a major industrial and agricultural state leading in the production of oil, cattle, sheep and cotton. All 254 counties of the state of Texas were used in this study.

3.2 Data Preparation

3.2.1 Temperature and Precipitation

Monthly precipitation and temperature grids for the period 1982 to 1999 were obtained from the Oregon State University PRISM group (http://prism.oregonstate.edu). These data have a spatial resolution of 2.5-arcmin (4 km) and contain monthly values in ASCII format. These data were used as inputs in the calculation of the monthly PDSI, SPI, Z-index, percent normal and deciles using a Fortran program. These indices' values were spatially averaged countywise by calculating the bounds of each county and averaging the interior pixel values. Figure 1 shows the spatial variation of the mean annual precipitation (spatially averaged countywise) over Texas.

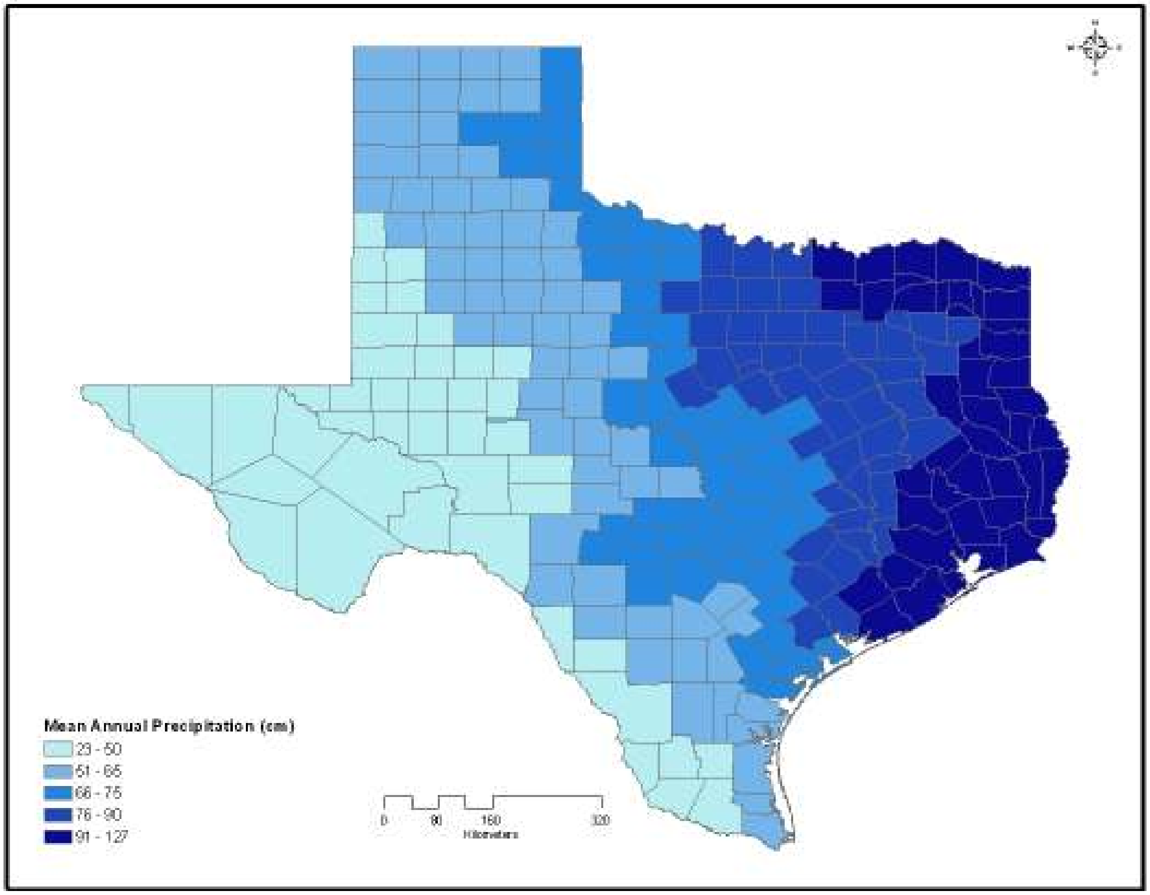

Figure 1 Spatial variation of mean annual precipitation across Texas

3.2.2 Available Water Holding Capacity (AWHC)

The Available Water Holding Capacity (AWHC) data for the US were obtained from the National Resources Conservation Service (NRCS) vendor's website (http://www.soilinfo.psu.edu/index.cgi?soil_data&conus&data_cov&awc&datasets&lam) in a raster format (1 km spatial resolution). Using this, AWHC values were aggregated to county level for Texas using a Texas county shapefile as a zone file and computing the zonal statistical average for the AWHC on the ArcGIS platform. The latitude of each Texas county was calculated by determining the centroid of each county's polygon. This information is a necessary input to the Fortran program computing the drought indices. Figure 2 depicts the spatial variation of mean AWHC across Texas.

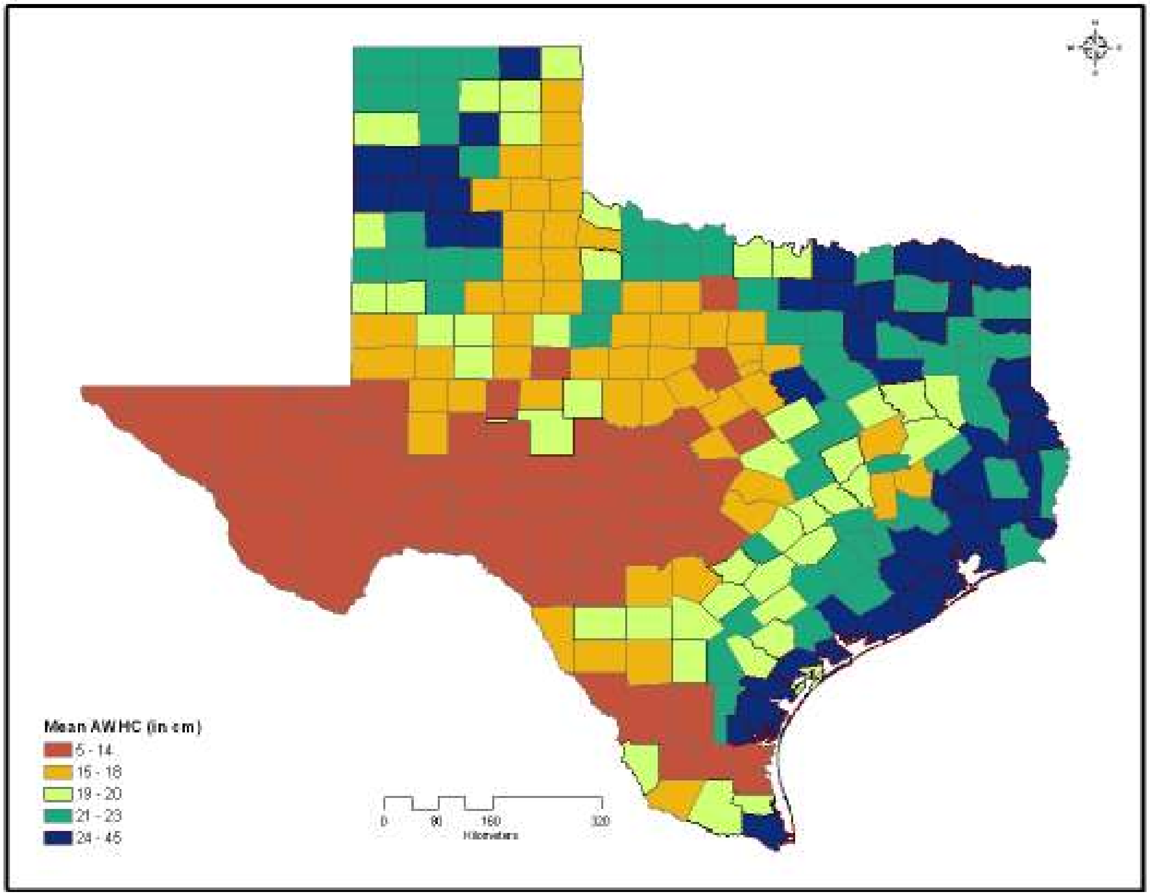

Figure 2 Spatial variation of mean AWHC across Texas

3.2.3 VCI

NDVI imagery at 8-km spatial resolution and 10 day temporal resolution was obtained from archives at the Goddard Earth Sciences, Distributed Active Archive Center (GES-DAAC) (http://daac.gsfc.nasa.gov). These images have already been atmospherically corrected for Rayleigh scattering and ozone absorption. After determining the maximum and minimum values of the NDVI over our temporal period of study (1982-1999), 10-day VCI values were computed for each of the months using

Equation (5) applying the Band Math tool in the ENVI software platform. These values were re-scaled to monthly VCI data by averaging the associated 10 day composites.

Finally, traditional drought indices (namely the Z-index, PDSI, 1-, 2-, 3-, 6-, 9-, 12-, 24-month SPI, percentile normal and deciles) and the VCI were extracted and compared during the months representing the period of maximum vegetation growth, that is, from March to August. This was done because the VCI, being an indicator of vegetation vigor, is only useful for monitoring drought conditions during the growing season (Vicente-Serrano 2007). Correlations between the VCI and each of the traditional drought indices were calculated using a linear regression model (Quiring 2003). The VCI validation statistics for each county against each of the traditional drought indices were then evaluated using the coefficient of determination (R^2). The overall model performance statistic was computed by taking the average R^2 of all the counties.

In order to investigate the spatial pattern in preliminary results, a number of additional variables were analyzed, including percentage area under irrigation, average soil moisture, water table depth, soil permeability rate, soil hydrologic group, soil drainage and landuse/landcover characteristics. They will be described in the following sections.

3.2.4 Percentage Under Irrigation

Data on estimated amounts of groundwater used for irrigation and area (in acres) of irrigation on a county-by-county, basin-wise basis since 1984 were obtained. These were compiled from the Texas Water Development Board (TWDB) Water Use Survey database which was obtained from the Groundwater Availability Modeling (GAM) resources website under the TWDB site (http://www.twdb.state.tx.us/gam/resources/resources.htm). These data were originally collected from National Resources Conservation Service (NRCS formerly SCS) and modified by TWDB staff. These data were summarized at the county level and aggregated temporally and normalized by county area to obtain the percentage of the county that is irrigated. Figure 3 represents the spatial variation of percentage irrigated area across Texas.

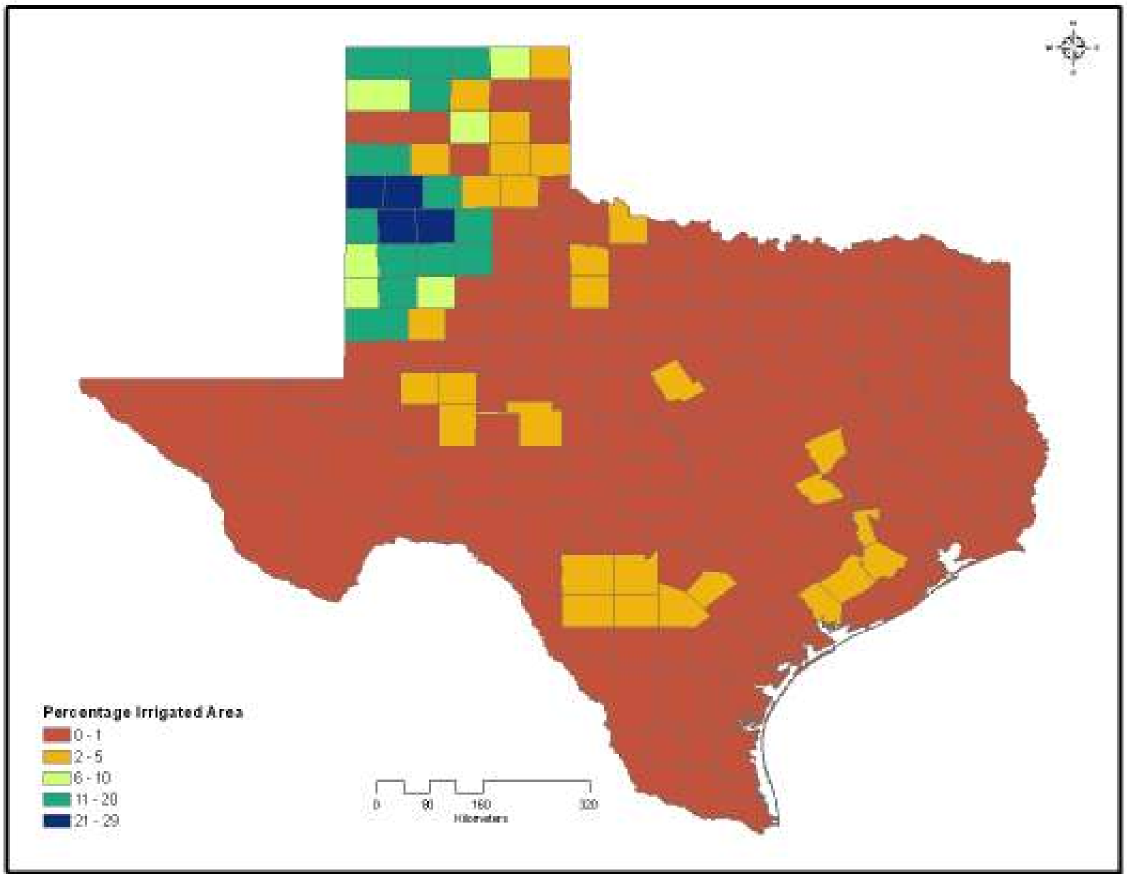

Figure 3 Spatial variation of counties' percentage irrigated area across Texas

3.2.5 Average Soil Moisture

A modified version of the climatic water budget (CWB) model (Mather 1978; Thornthwaite 1948, 1955) was used as the basis for a soil moisture computational program in Fortran language developed by Hawkins (2006). This model required monthly temperature and monthly precipitation data (obtained from the PRISM group used earlier in this study) and AWHC values (in units of mm/m) were obtained from The Pennsylvania State University (PSU) Soil Information for Environmental Modeling Ecosystem Management site (http://www.soilinfo.psu.edu/indeg.cgi). These data were created from the STATSGO database. Soil moisture rasters (in units of mm per 1.6 m) were created for all of continental United States for each month of the years 1982-1999. Using a shapefile of counties of Texas, zonal statistics of each raster within the growing season (March to August) were calculated and temporally averaged to obtain the average soil moisture for each county over period under study (1982-1999). The spatial variation of the mean soil moisture across Texas is shown in Figure 4.

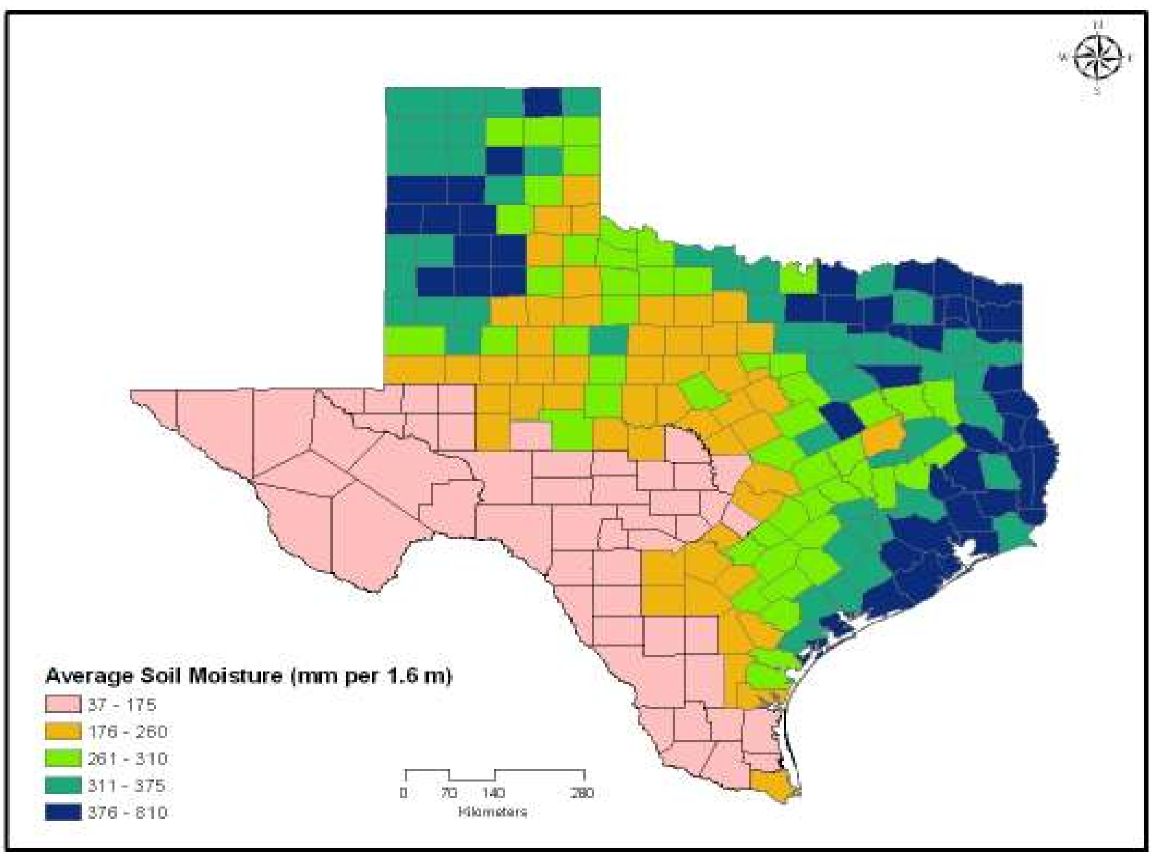

Figure 4 Spatial variation of mean soil moisture across Texas

3.2.6 Soil Properties

The STATSGO soil database at The Pennsylvania State University (PSU) Soil Information for Environmental Modeling Ecosystem Management (http://www.soilinfo.psu.edu/etc/statsgolist.cgi?statename=Texas) contains a database of shapefiles delineating the state of Texas into Map units which are comprised of multiple components (unknown spatial distribution) which are further divided into vertically stacked map layers. This database was used to extract the soil properties variables: permeability rate, water table depth, hydrologic groups and soil drainage.

Permeability Rate

For the component with maximum component percentage, the topmost layer was extracted and the average of minimum and maximum value of the range for the soil layer or horizon, expressed as inches/hour was assumed to be the permeability rate for that map unit. The shape file was rasterized and county-wise mean zonal statistics were obtained to get the averaged permeability rate for each county. Figure 5 depicts the spatial variation of the permeability rate across Texas.

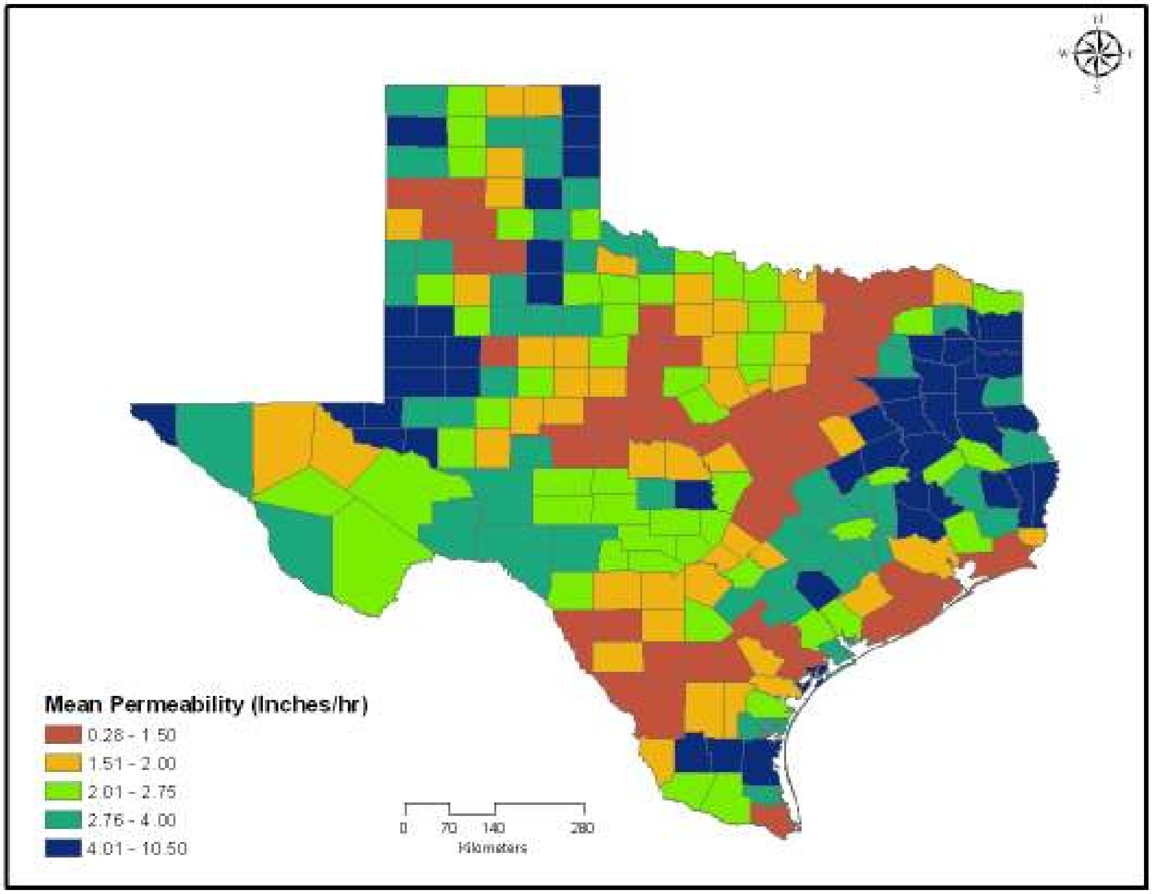

Figure 5 Spatial variation of mean permeability across Texas

Water Table Depth (m)

The average of the seasonal maximum and minimum values of water table depth for each majority component were assumed to be the water table depth for that map unit. The shape file was rasterized and county wise mean zonal statistics were obtained to get the averaged water table depth for each county. Figure 6 shows the variation of the mean water table depth across Texas.

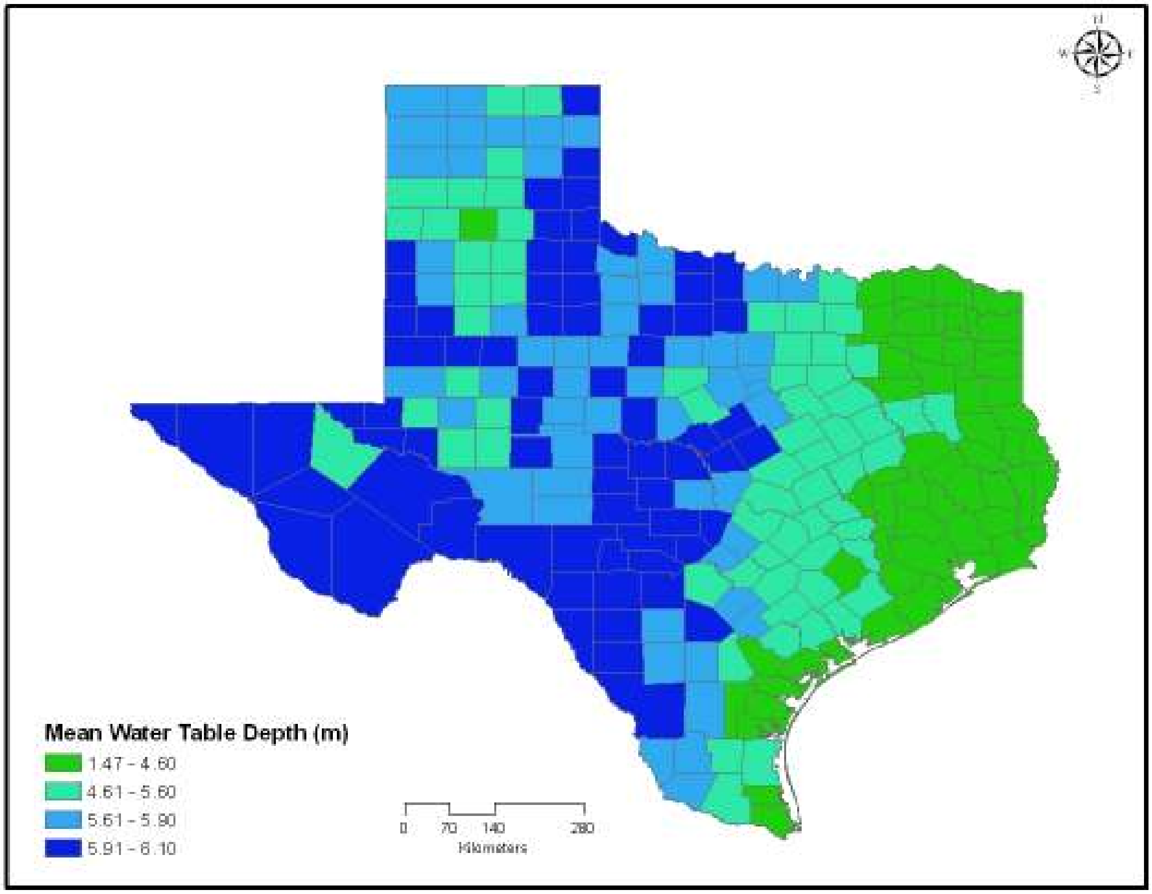

Figure 6 Spatial variation of mean water table depth across Texas

Hydrologic Groups

The hydrologic group of the dominant component was assumed to be the representative hydrologic group of the map unit. The shape file was rasterized and county wise majority zonal statistics were obtained to get the dominant hydrologic soil group for each county. The values were recoded to a nominal scale: existing categories of A = sandy, free draining soil, B and C = intermediate soil groups and D = clayey, poorly drained soils, were recoded to 1, 2, 3 and 4 respectively. Figure 7 shows the spatial variation of dominant hydrologic soil group across Texas.

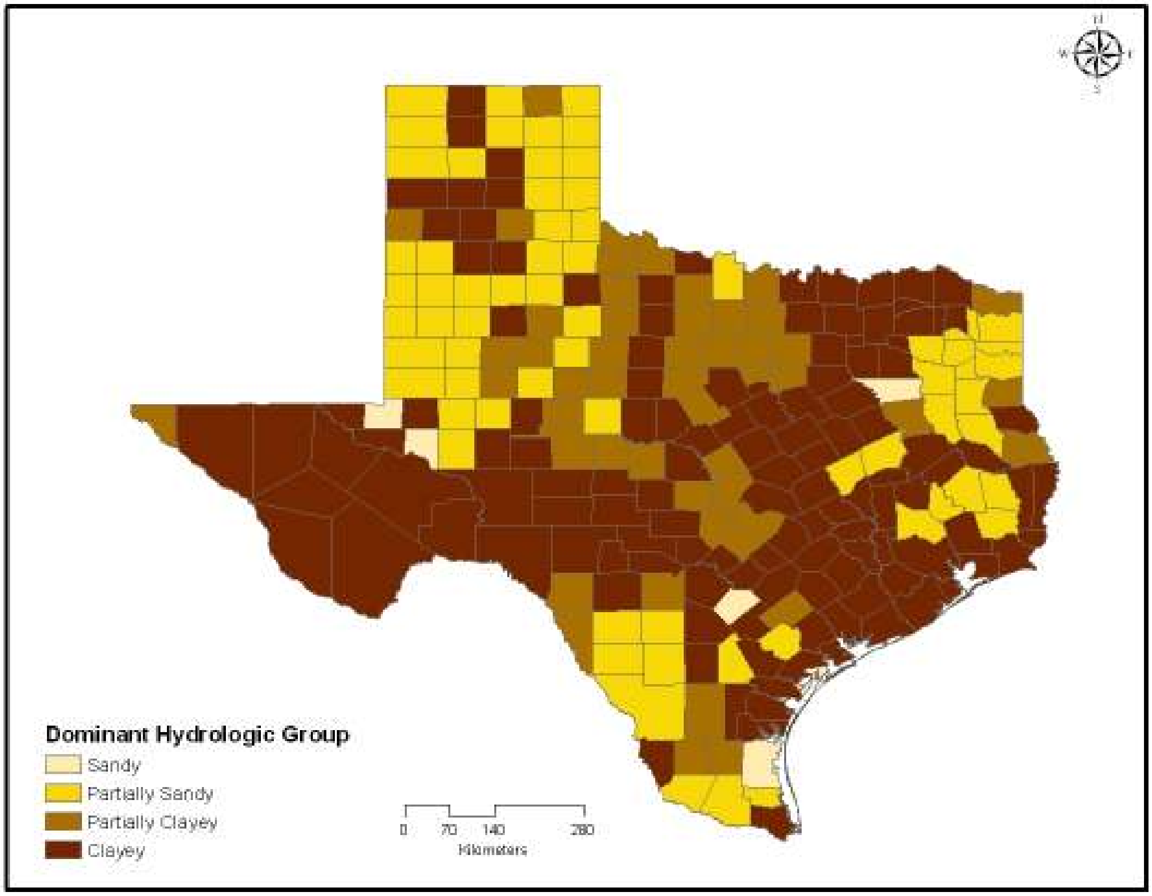

Figure 7 Spatial variation of dominant hydrologic soil group across Texas

Soil Drainage

The alphabetic codes in the drainage field of the database identify the natural drainage condition of the soil and refer to the frequency and duration of periods when the soil is free of saturation. The seven groups Well Drained (W); Excessive (E); Moderately Well (MW); Poorly (P); Somewhat Excessively (SE); Somewhat Poorly (SP) were recoded into the nominal scale groups of 1, 7, 3, 4, 6 and 5 respectively and the drainage group of the dominant component was assumed to be the group of the map unit. The shape file was rasterized and county wise majority zonal statistics were obtained to get the dominant drainage group for each county. Figure 8 shows the spatial variation of dominant soil drainage class across Texas.

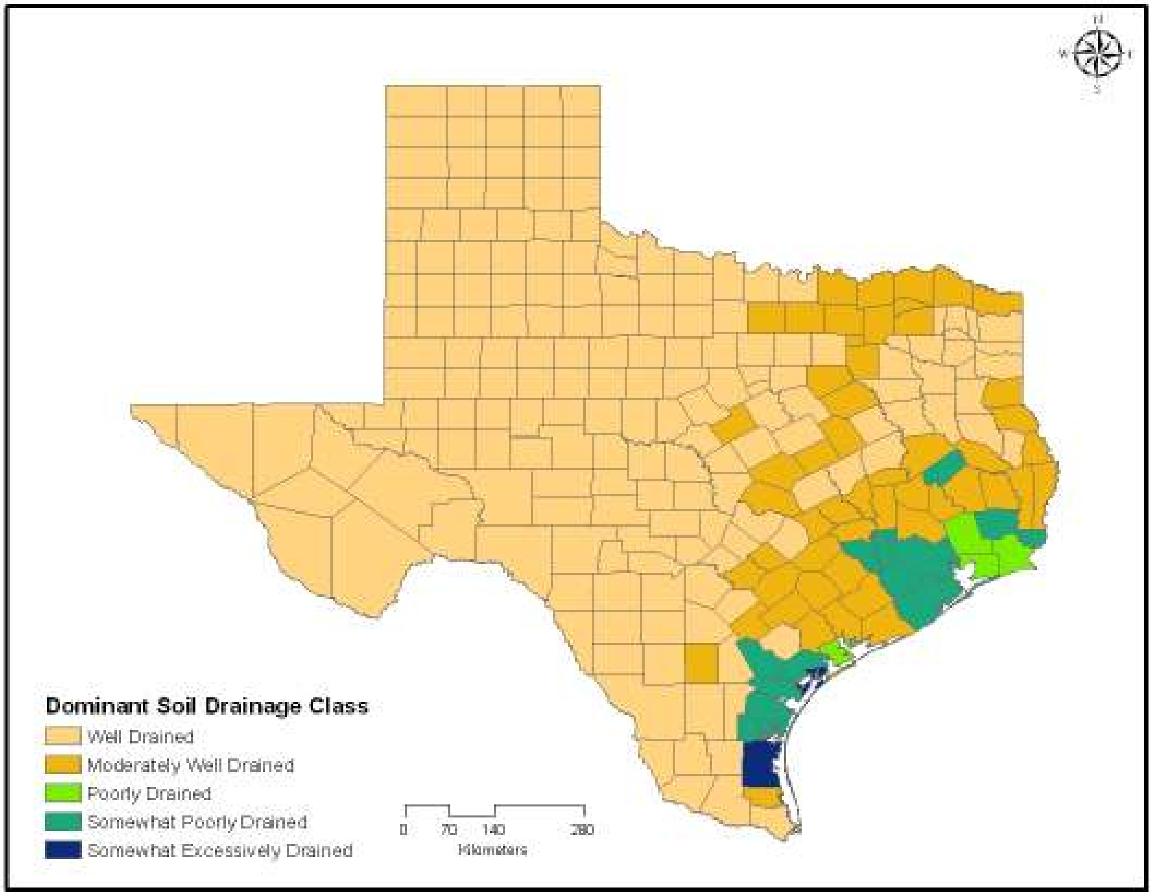

Figure 8 Spatial variation of dominant soil drainage class across Texas

3.2.7 Landuse and Landcover (LULC)

Preclassified landuse and landcover shapefile data from the USGS (http://landcover.usgs.gov/show_data.php?code=setx&state=Texas_se) were obtained and nine broad categories of landuse were identified in accordance with U.S. Geological Survey Land Use and Land Cover Classification System for Use with Remote Sensor Data: Urban land, Agricultural land, Rangeland, Forest Land, Water, Wetland, Barren Land, Tundra and Perennial Snow/Ice. These were recoded into a nominal scale from 1 to 9 respectively, rasterized and zonal majority statistics were obtained to get the dominant landuse category for each county. Additionally, minority zonal statistics were computed to get the minority landuse category for each county as an extra variable for analysis. Figure 9 shows the spatial variation of dominant landuse/landcover type across Texas.

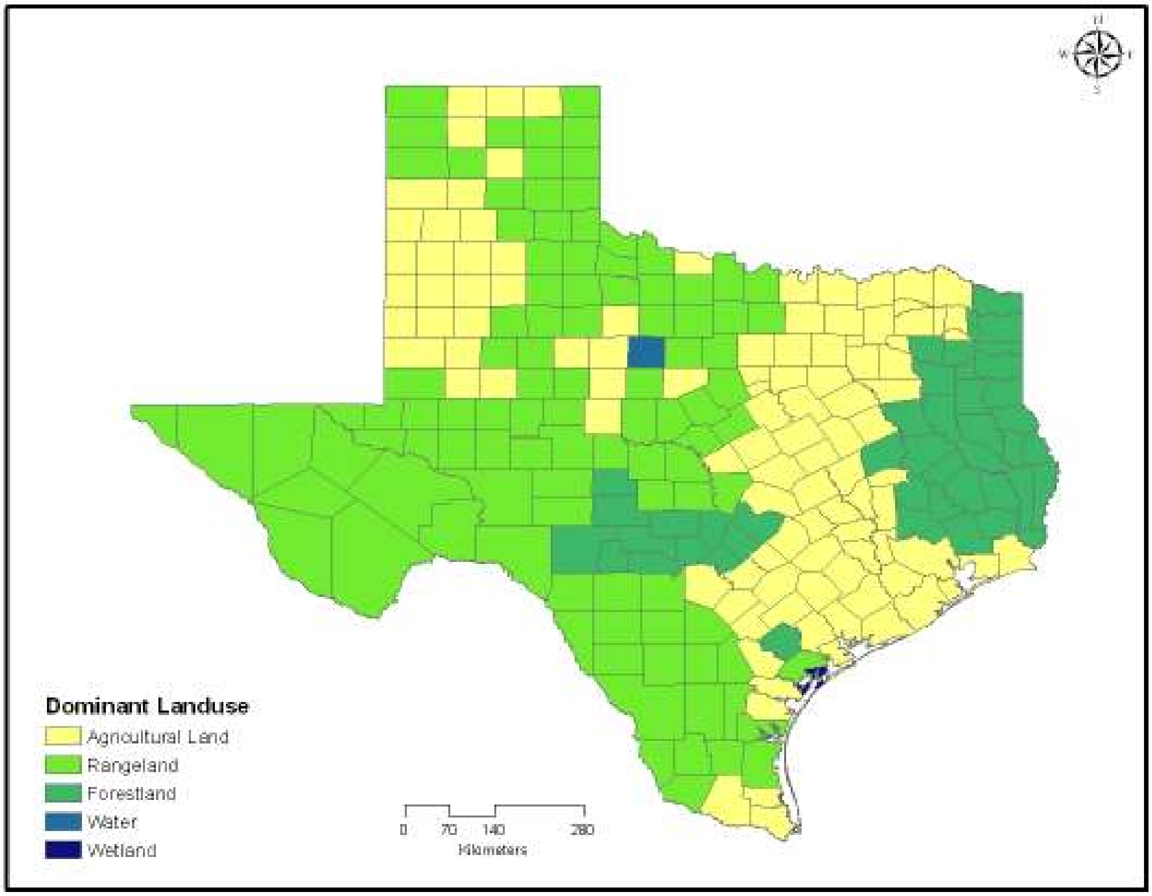

Figure 9 Spatial variation of dominant landuse/landcover type across Texas

4. RESULTS

The coefficient of determination (R^2) describes the fraction of the total variation in the observed data that is explained by the model. It ranges from 0 to 1 with higher values indicating more variance explained. However, studies summarized in Legates (1999) show that this statistic has a number of limitations such as assumption of a linear relationship between the variables and extreme sensitivity to outliers and these limitations are kept in regard in our final assessment of the model performance.

The overall model performance statistics for all the counties are summarized in Table 1. The 6-month SPI bears the strongest correlation with the VCI with an R^2 = 0.287. The PDSI follows next with an R^2 = 0.256 and the 9-month SPI is a close third. The 3-month, 12-month, 2-month and 24-month SPI are ranked next. The Z-index, percent normal and deciles are only weakly correlated with the VCI.

Table 1 Mean relationship between VCI and meteorological drought indices (n = 254)

Drought Index	R^2
6-month SPI	0.287
PDSI	0.256
9-month SPI	0.255
3-month SPI	0.202
12-month SPI	0.200
2-month SPI	0.150
24-month SPI	0.124
Z-index	0.110
Deciles	0.048
1-month SPI	0.042
Percent Normal	0.033

4.1 Spatial Variability of the Model Performance

Figure 10 shows that there is a strong spatial variation in the degree of correlation (R^2) between the VCI and the 6-month SPI which results in an increasing gradient map from east/south-east to west/north-west. Brazoria, Montgomery and Harding counties in east Texas have a coefficient of determination that is near zero, while Maverick, Borden and McMullen counties in central and western Texas have an $R^2 > 0.6$.

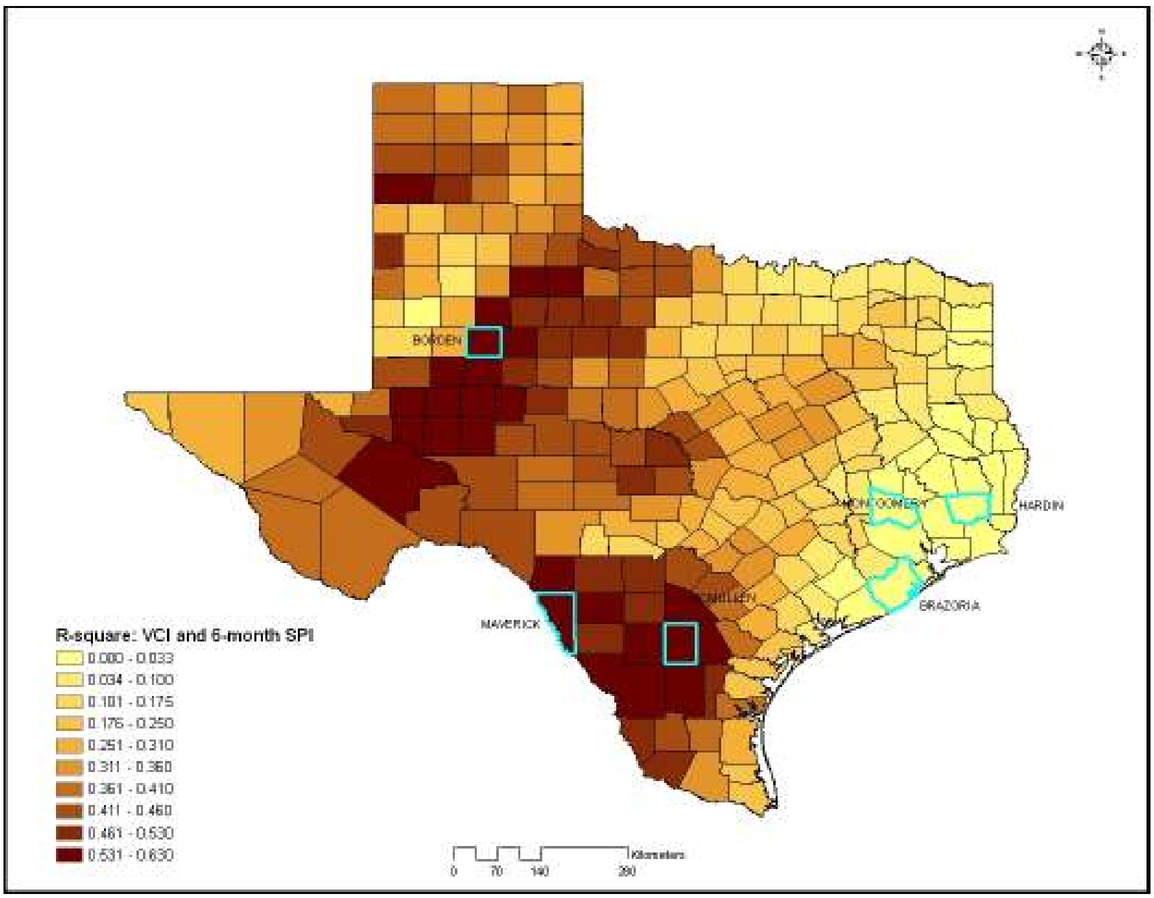

Figure 10 Spatial variation of R^2 (VCI and 6-month SPI) over Texas

Figure 11 shows a east to west gradient in the R^2 between VCI and PDSI. Brazoria county has the lowest R^2 and Upton, Reeves and Pecos counties in west Texas have the highest R^2 values.

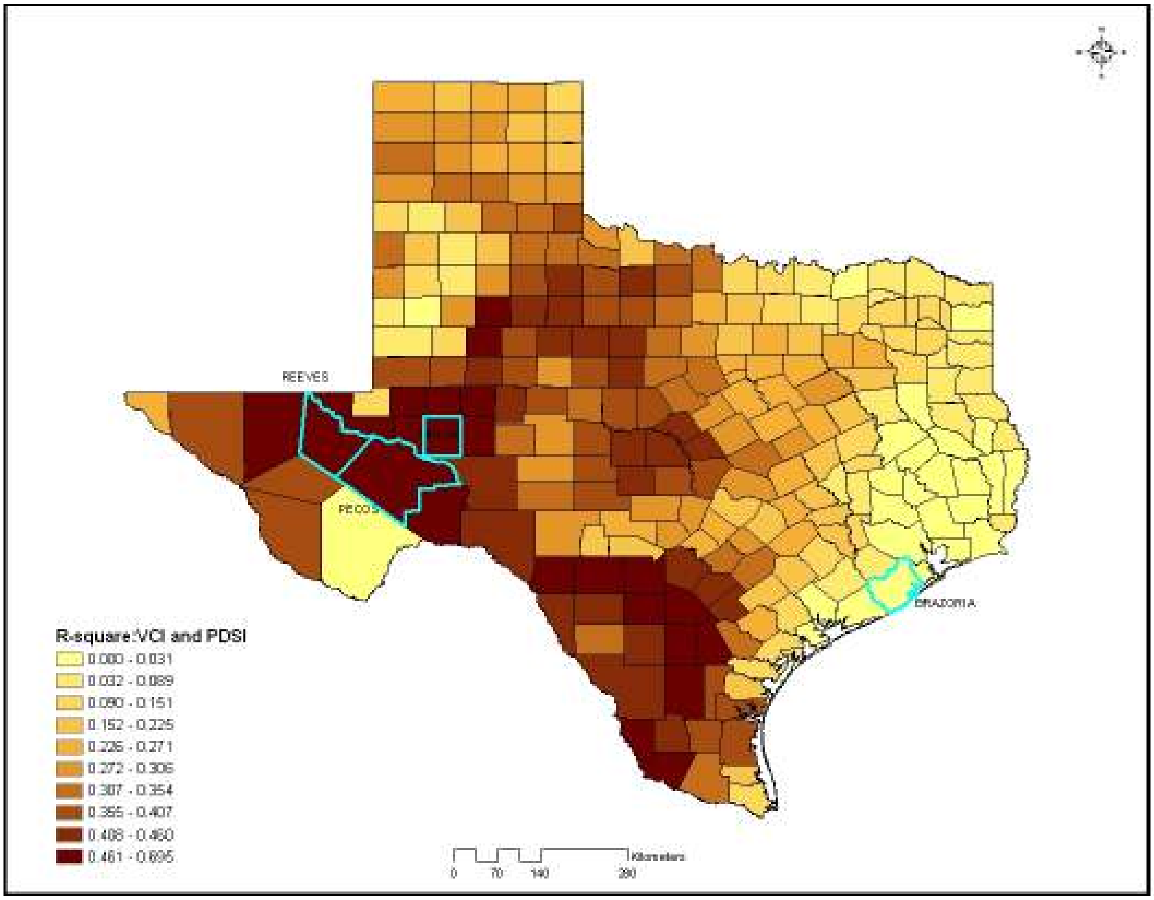

Figure 11 Spatial variation of R^2 (VCI and PDSI) over Texas

Figure 12 shows a similar spatial signal to Figure 11. There is a definite gradient in the correlation coefficient from east to west. Harding county has minimum R^2 while Upton, Reagan and Pecos in west Texas have maximum R^2.

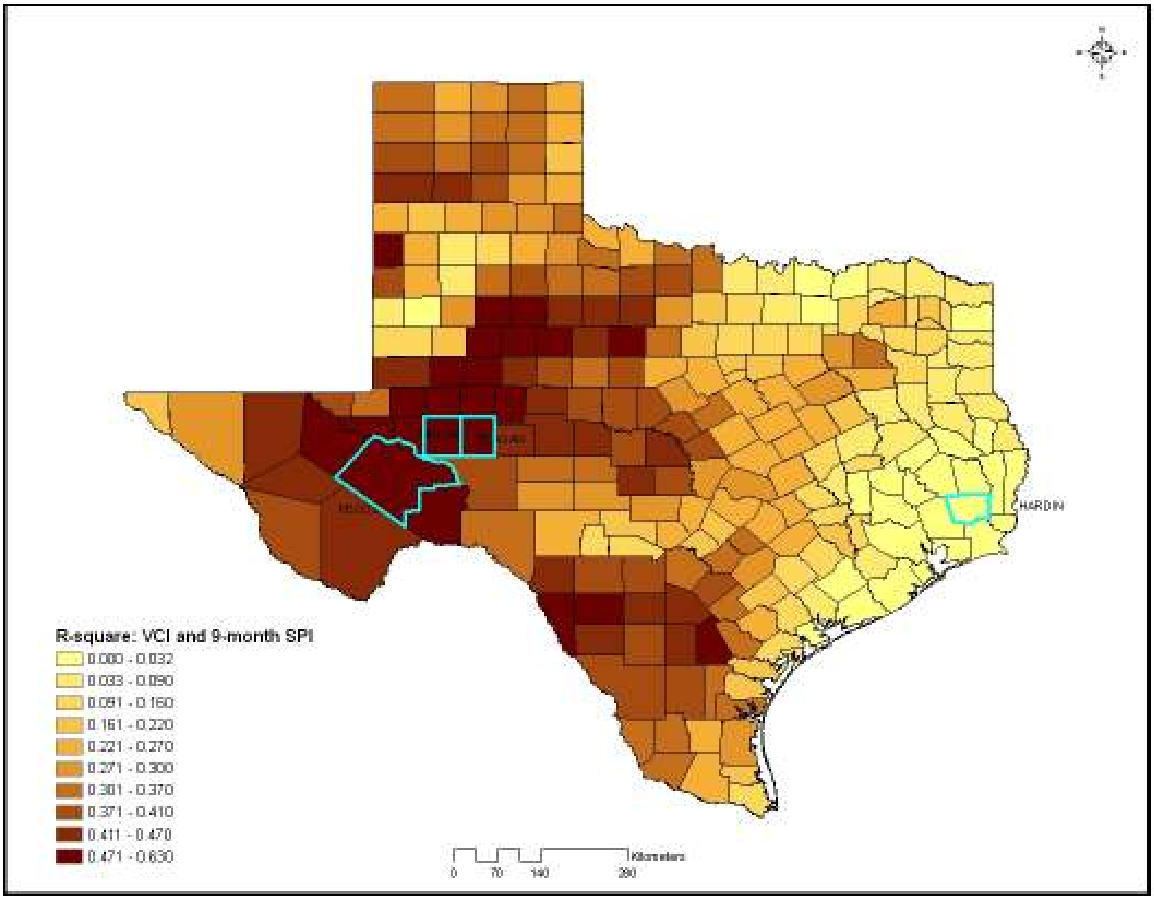

Figure 12 Spatial variation of R^2 (VCI and 9-month SPI) over Texas

4.2 Temporal Variability of Model Performance

The variation of VCI and the other drought indices over the entire growing season time period was plotted for Pecos County (this county in west Texas consistently showed high R^2 correlations for all indices).

As observed from Figures 13-16, the 3- and 12-month SPI have a high degree of scatter as compared to the 6- and 9-month SPI vs VCI plots and consequently lower R^2.

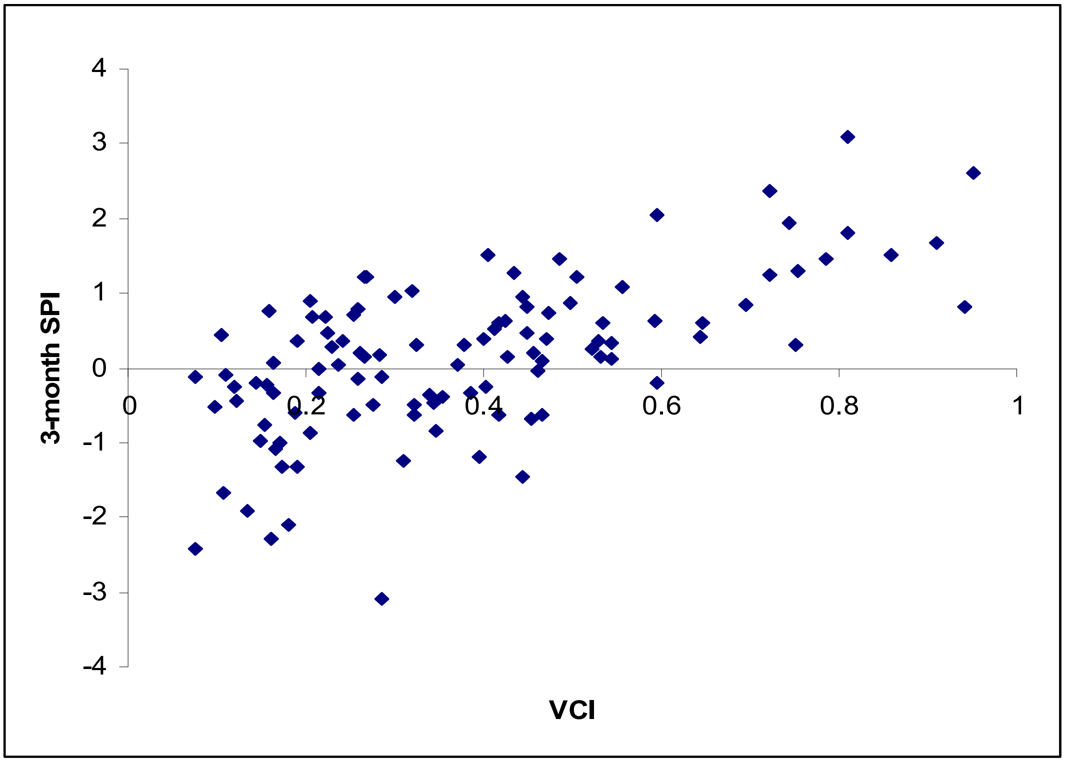

Figure 13 Temporal variation of VCI and the 3-month SPI in Pecos County

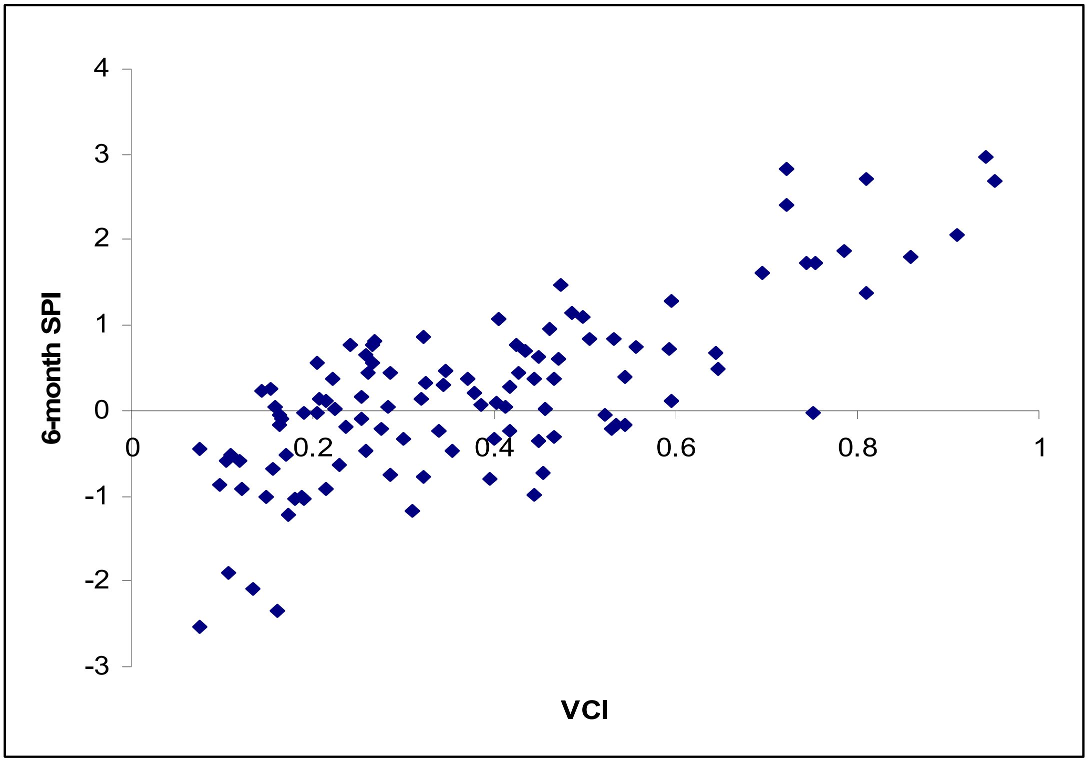

Figure 14 Temporal variation of VCI and the 6-month SPI in Pecos County

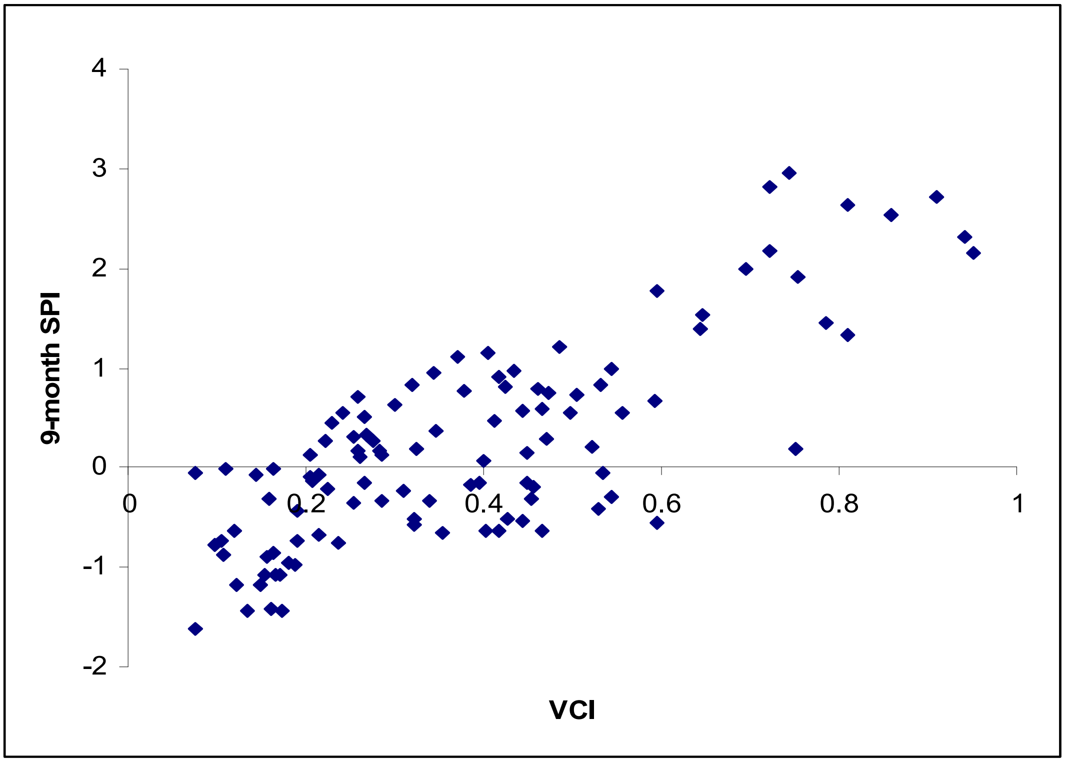

Figure 15 Temporal variation of VCI and the 9-month SPI in Pecos County

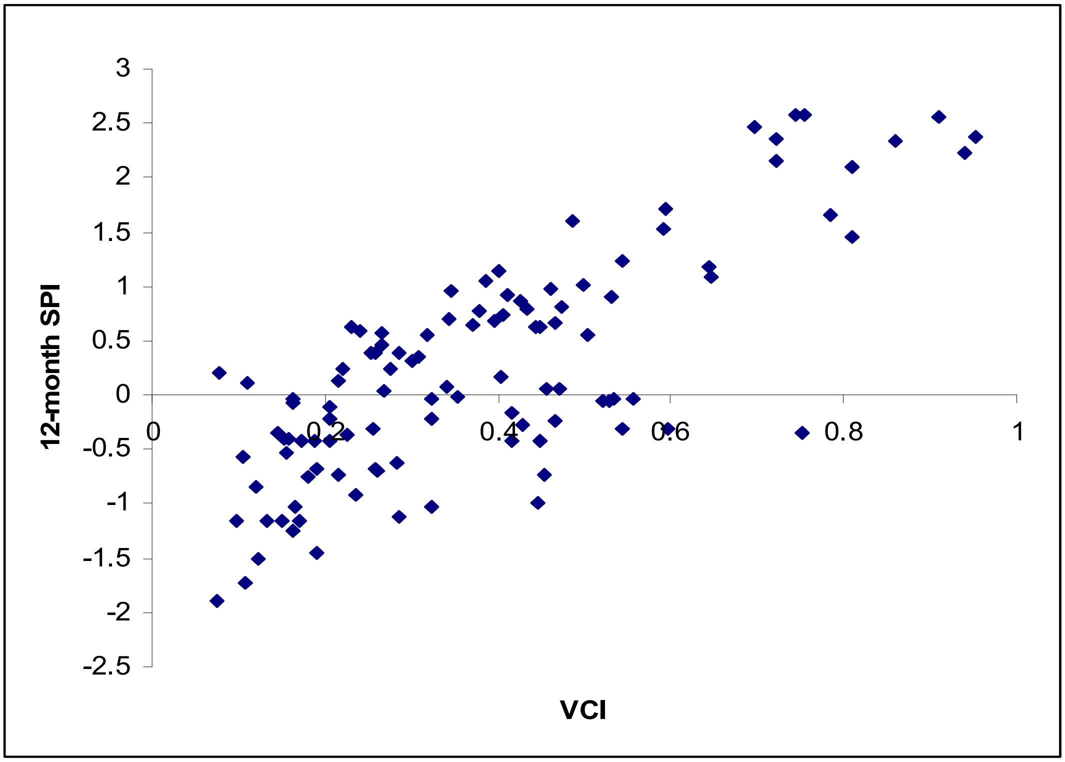

Figure 16 Temporal variation of VCI and the 12-month SPI in Pecos County

As seen in Figure 17, there is more scatter and consequently a lower R^2 in the VCI-Z-index model.

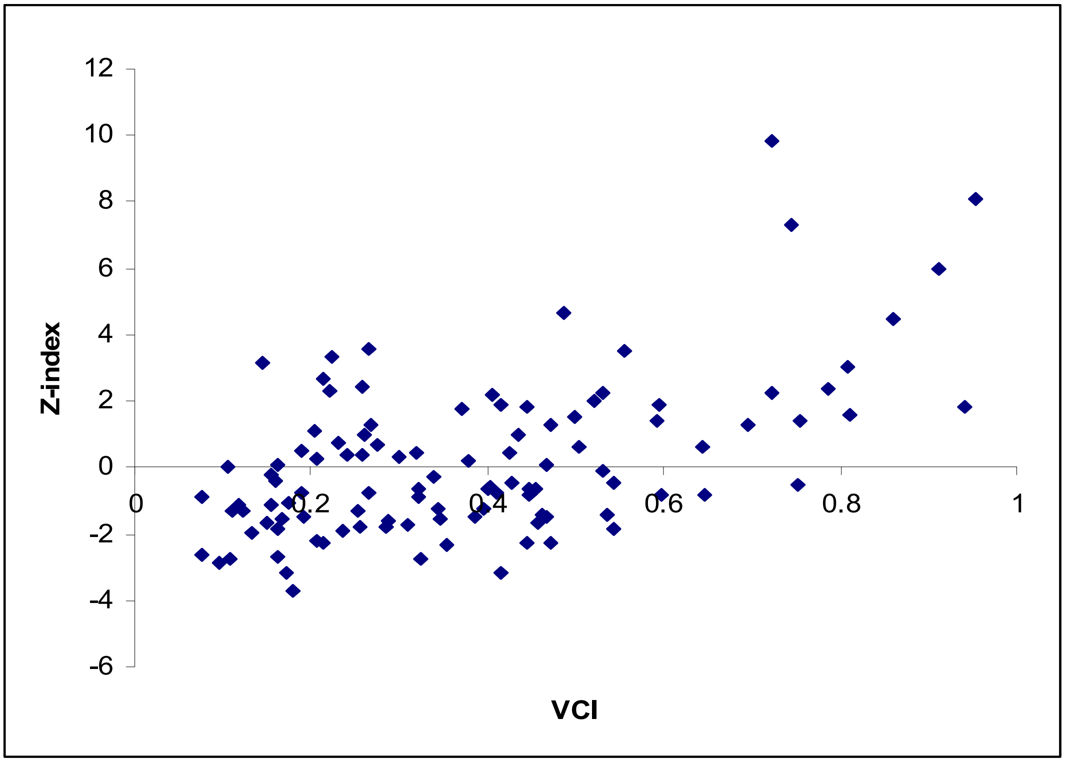

Figure 17 Temporal variation of VCI and the Z-index in Pecos County

The VCI-PDSI signal (Figure 18) is a recursive relation, accounting for antecedent moisture conditions. Vegetation also responds gradually to any changes in climate. This could explain the high degree of correlation obtained between the two. Figures 15, 16 and 17 show a similar amount of scatter as they account for antecedent moisture conditions.

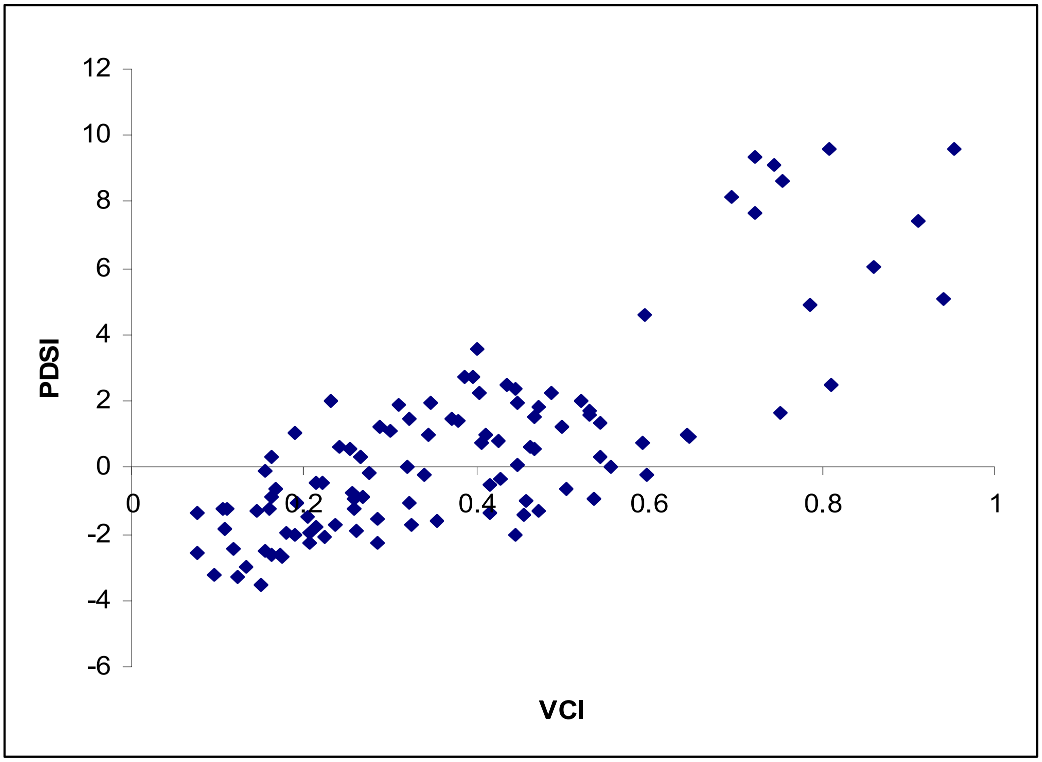

Figure 18 Temporal variation of VCI and the PDSI in Pecos County

4.3 Discussion of Stage 1 Results

The VCI shows the strongest correlation with the 6-month SPI and the PDSI. The SPI is a probability-based index taking into account the entire historical range of the precipitation. The VCI, similarly, is the normalization of the current vegetation health by its complete historical range. The PDSI, being heavily weighed by antecedent conditions of moisture, also shows a close correlation with the VCI. The VCI is unable to track the short-term varying Z-index (which is dependent only on the current month precipitation statistics) and also the 1- and 2-month SPI. This suggests that VCI has a similar response to only those traditional drought indices which account for antecedent precipitation conditions for the last 6 to 9 months. This is understandable because only locations with sustained precipitation can support dense photosynthetic vegetation.

5. INVESTIGATION OF SPATIAL PATTERNS

The strong spatial coherence of the VCI-drought index correlations suggests that factors other than the moisture conditions may be important. Investigation into soils, area under irrigation and landuse/landcover data for Texas, among other factors, may yield insight into this pattern. A multivariate regression model incorporating the above data at a monthly temporal resolution is designed. One must also note that our reporting is at the county level which is a political delineation and not a physical or ecological boundary and loss of information due to this spatial averaging may be significant. Recent studies (Vicente-Serrano 2007) in the region north-east to the Iberian Peninsula (France) have shown that the effect of drought on vegetation cover varies significantly spatially and temporally, the magnitude of the drought being influenced by the local landcover types and seasonal variations. Vicente-Serrano (2007) reported that aridity and vegetation characteristics account partially for the varying spatial influence of drought on vegetation health. As such, additional variables are investigated in our study to explain the spatial pattern observed in the correlation between the VCI and traditional drought indices.

5.1 Multivariate Model Evaluation and Performance

The additional ten variables (precipitation, AWHC, percentage area under irrigation, average soil moisture, water table depth, soil permeability rate, soil hydrologic group, soil drainage and majority/minority landuse/landcover characteristics) were entered as independents into a forwardstep multivariate regression model on the SAS-JMP Enterprise Miner statistical analysis software platform. The independent variable was the R^2 for VCI vs PDSI because this drought index had strong mean correlation with the VCI. The categorical variables as nominal variables (e.g., the soil drainage groups were given numbers from 1 to 7 where the numbers do not represent any hierarchy of draining ability) rather than ordinal variables. Additionally, to study any possible correlation among the independent variables, a correlation matrix was also generated from the ten variables (summarized in Table 7) to identify collinearity issues.

Note that although monthly precipitation is used to calculate the PDSI, here we are using mean annual precipitation to represent the climate of the county. Also fundamentally, precipitation influences the water table depth and possibly the percentage of irrigation in each county. Hence two separate models were run, one with precipitation, and one without precipitation, in order to eliminate any problems with collinearity. In addition to the R^2, Mallows Cp is also calculated to assess over-fitting and obtain a model with the least correlated independent variables. Mallow's Cp is defined as:

$$Cp = \sum (y - y_p)^2 / s^2 - n + 2p \tag{6}$$

where y_p is the predicted value of y from the p regressors, s^2 is the residual mean square after regression on the complete set of k and n is the sample size.

If Cp is plotted against p, Mallows (1973) recommends choosing the reduced model where Cp first approaches p. Table 4, which summarizes the regression model with mean annual precipitation included, shows that Cp approaches the value 9 (the number of regressors) at the addition of the first 5 variables. Table 9 also shows that the mean AWHC variable is highly correlated (correlation coefficient = 0.91) with the average soil moisture. Hence the mean AWHC variable should be excluded from all three of our models. Hence model 1 with only the first 5 variables would be the most reduced model. Similiarly from Table 6, model 2 would be the most reduced with the inclusion of the first 4 variables and a reduced model 3 (Table 8) would have 4 variables. However the number of regressors to include in the model was decided on the basis of their probability significance level to accommodate all the investigative variables.

Table 2 shows the results obtained by fitting a multiple regression model to explain the spatial variations in the relationship between PDSI and the VCI (Model 1). A second model was fit excluding precipitation (Model 2). Model 1 has 9 variables namely mean precipitation, percentage area under irrigation, average soil moisture, water table depth, soil permeability rate, AWHC, majority landuse/landcover characteristics and two soil drainage group combinations. The F Ratio in Table 3 shows the significance of the 9 variables (some split into subgroups) in Model 1.

Model 2 has 8 variables namely percentage area under irrigation, average soil moisture, water table depth, soil permeability rate, AWHC, soil drainage, majority LULC and minority LULC groups. The F Ratio in Table 5 shows the significance of the 8 variables (some split into subgroups) in Model 2.

An additional model with variables representing the percentage abundance of each of the seven LULC classes in each county instead of the majority LULC variable was also run (Model 3). The F Ratio in Table 7 shows the significance of the variables in Model 3. The results of the model are summarized in Table 8.

Table 2 Summary of multiple regression models

Model	MSE	R^2	R^2 Adjusted
1. All 9 variables	0.007	0.7356	0.7258
2. Only 8 variables	0.008	0.6916	0.6762
3. LULC modified	0.010	0.6143	0.6001

Table 3 Forward stepwise regression of R^2 (VCI-PDSI) against all variables (Model 1)

Parameter	Estimate	"F Ratio"
Intercept	0.480	0
Percentage County Irrigated	-0.008	26.881
MAJ_hydgrp[4&2-1&3]	0	0.015
MAJ_hydgrp[4-2]	0	0.091
MAJ_hydgrp[1-3]	0	0.155
MAJORITY_LULC[6&4&2-3&5]	-0.030	17.639
MAJORITY_LULC[6&4-2]	0	0.048
MAJORITY_LULC[6-4]	0	0.381
MAJORITY_LULC[3-5]	0	0.036
MINORITY_LULC[3&7&5-6&1&4&2]	0	0.629
MINORITY_LULC[3&7-5]	0	0.502
MINORITY_LULC[3-7]	0	1.206
MINORITY_LULC[6&1&4-2]	0	0.928
MINORITY_LULC[6-1&4]	0	0.754
MINORITY_LULC[1-4]	0	0.753
MAJdrainage[4&5&3-6&1]	-0.037	3.154
MAJdrainage[4-5&3]	0	0.032
MAJdrainage[5-3]	0	0.556
MAJdrainage[6-1]	0.041	1.560
Mean Permeability	-0.021	36.874
MAJORITYhydr[2&4&1-3]	0	0.048
MAJORITYhydr[2-4&1]	0	0.174
MAJORITYhydr[4-1]	0	0.230
Water Table Depth	0.024	7.499
Mean AWHC	0.004	3.218
Mean Annual Precipitation	-0.003	51.482
Mean Soil Moisture	-0.001	5.083

Table 4 Model 1 step history

Step	Parameter	R^2	Cp
1	**Mean Annual Precipitation**	0.5297	173.560
2	**Percentage County Irrigated**	0.6236	90.968
3	**Mean Permeability**	0.6795	42.626
4	**MAJORITY_LULC[6&4&2-3&5]**	0.7102	17.041
5	**Water Table Depth**	0.7241	6.470
6	**MAJdrainage[4&5&3-6&1]**	0.7289	4.168
7	**Mean Soil Moisture**	0.731	4.295
8	**Mean AWHC**	0.7339	3.701
9	**MAJdrainage[6-1]**	0.7356	4.179

Table 5 Forward stepwise regression of R^2 (VCI-PDSI) against all variables excluding precipitation (Model 2)

Parameter	Estimate	"F Ratio"
Intercept	0.176	0
Percentage County Irrigated	-0.003	4.747
MAJ_hydgrp[4&2-1&3]	0	0.544
MAJ_hydgrp[4-2]	0	0.362
MAJ_hydgrp[1-3]	0	0.934
MAJORITY_LULC[6&4&2-3&5]	-0.052	21.286
MAJORITY_LULC[6&4-2]	-0.020	4.311
MAJORITY_LULC[6-4]	0	0.244
MAJORITY_LULC[3-5]	0	0.001
MINORITY_LULC[3&7&5-6&1&4&2]	0.006	1.535
MINORITY_LULC[3&7-5]	-0.002	2.162
MINORITY_LULC[3-7]	0.025	3.935
MINORITY_LULC[6&1&4-2]	0	0.06
MINORITY_LULC[6-1&4]	0	0.037
MINORITY_LULC[1-4]	0	0.032
MAJdrainage[4&5&3-6&1]	-0.059	5.994
MAJdrainage[4-5&3]	0	0.009
MAJdrainage[5-3]	0	0.074
MAJdrainage[6-1]	0.066	3.472
Mean Permeability	-0.015	16.230
MAJORITYhydr[2&4&1-3]	0	0.613
MAJORITYhydr[2-4&1]	0	0.446
MAJORITYhydr[4-1]	0	0.296
Water Table Depth	0.041	16.738
Mean AWHC	0.008	9.234
Mean Soil Moisture	-0.001	33.948

Table 6 Model 2 step history

Step	Parameter	R^2	Cp
1	**Mean Soil Moisture**	0.4673	150.860
2	**MAJORITY_LULC[6&4-2]**	0.6071	49.619
3	**Water Table Depth**	0.6395	27.298
4	**Mean Permeability**	0.6562	16.709
5	**Mean AWHC**	0.6661	11.287
6	**MAJdrainage[6-1]**	0.6801	4.758
7	**Percentage County Irrigated**	0.6857	2.540
8	**MINORITY_LULC[3-7]**	0.6916	4.104

Table 7 Forward stepwise regression of R^2 (VCI-PDSI) against variables with modified LULC variable (Model 3)

Parameter	Estimate	"F Ratio"
Intercept	0.535	0.000
Percentage County Irrigated	0.000	0.732
MAJ_hydgrp[4&2-1&3]	0.000	0.707
MAJ_hydgrp[4-2]	0.000	0.662
MAJ_hydgrp[1-3]	0.000	0.716
MAJdrainage[4&5&3-6&1]	-0.068	9.960
MAJdrainage[4-5&3]	-0.047	2.573
MAJdrainage[5-3]	-0.020	1.508
MAJdrainage[6-1]	0.000	0.257
Mean Permeability	-0.020	24.394
Mean Soil Moisture	-0.001	107.724
Perc Urban Land	-0.003	3.143
Perc Agricultural Land	-0.001	1.521
Perc Rangeland	0.002	0.002
Perc Forest Land	-0.002	3.781
Perc Water	0.000	0.001
Perc Wetland	0.000	0.036
Perc Barren Land	0.000	0.128

Table 8 Model 3 step history

Step	Parameter	R^2	Cp
1	Mean Soil Moisture	0.4673	81.679
2	Perc Forest Land	0.5200	50.894
3	MAJdrainage[4&5&3-6&1]	0.5549	31.155
4	Mean Permeability	0.5825	15.974
5	Perc Rangeland	0.6009	6.496
6	MAJdrainage[5-3]	0.6091	5.358
7	Perc Urban Land	0.6119	5.656
8	Perc Agricultural Land	0.6143	6.159

5.2 Discussion of Results

As seen from Table 2, Model 1 accounts for 73.56% of the variance in the relationship between VCI and PDSI. The forward stepwise regression accepts only regressor terms at a probability significance level of 0.25 ensuring that only the most significant variables are retained in the model and the relevance of these is discussed in their order of importance.

The most significant variable is mean annual precipitation. It appears that VCI is most strongly correlated with traditional drought indices (e.g., PDSI) in counties that have a semi-arid climate. This may be a function of the type of vegetation that grows in these counties or it may be a result of the vegetation in these semi-arid regions being particularly sensitive to moisture stress (since PET typically exceeds P in these regions during the growing season). Percentage irrigation is the next most significant contributor to this model. The negative sign of the estimate (indicative of a negative correlation) shows that the VCI is most strongly correlated with drought indices in counties that have a low percentage of irrigation. There is a disconnect between the VCI and the PDSI in counties with high amounts of irrigation because the vegetation (crops) are irrigated and so VCI may be high even in years that receive small amounts of precipitation (e.g., classified as dry according to PDSI). The mean permeability in the soil is found to be negatively correlated.

The landuse/landcover is the next most significant variable and since this a non-binary nominal variable in a multivariate regression, SAS analyzes it a unique way. The levels of the nominal variable are considered in some order and a split is made to make the two groups of levels that most separate the means of the response. Then each subgroup is further divided into its most separated subgroups, and so on, until all the levels are distinguished into (k-1) terms for k levels. In processing the MAJORITY_LULC variable, SAS splits it into all possible binary groups and extracts the grouping that produces the most distinct change in the response. Then for each of the two groups identified, further subgroups are structured which give the most change in the response. This means that the clubbed binary group consisting of forest&agricultural&wetland - rangeland&water (represented by MAJORITY_LULC[6&4&2-3&5] in Table 4), is the most significant combination. This is expected, since rangeland is sparsely vegetated and waterbodies are completely devoid of vegetation, their surface spectral signature is unresponsive (relative to the group of forest&agricultural&wetland) to any drought conditions although the water bodies' size may change. Within the first group however, wetlands and agricultural lands are most distinct in their contribution towards the correlation between the indices. This is understandable as wetland vegetation is supported by presence of waterbodies while agricultural crops generally have shallow roots which makes them more susceptible to drought conditions. This type of binary splitting of nominal variables by the SAS program produces results that are difficult to interpret and hence a variable on the percentage abundance of LULC variable is used instead in Model 3. The mean water table depth shows strong positive correlation indicating that in counties where the water table is far below the surface, the vegetation is more susceptible to drought influence (e.g., vegetation may be unable to tap into a deep water table and therefore unable to buffer itself against a lack of precipitation). The soil-drainage group consisting of *Poorly & Somewhat Poorly & ModeratelyWell - Somewhat Excessive & Well Drained* (represented by MAJdrainage[4&5&3-6&1] in Table 4) is the most significant combination with the soil groups clearly arranged in a hierarchical order of drainage even though the variables were entered as nominal without any order of ranking. Since SAS analyses nominal variables at a binary level, this order of splitting the drainage variables produces the greatest variation in the response variable. The average soil moisture shows a negative correlation indicating that soils with low soil moisture cannot protect the vegetation from drought. The mean AWHC shows a strong positive correlation. The soil-drainage variable group of Somewhat Excessively and Well Drained appears again as the last variable (MAJdrainage[6-1] in Table 4) but this can be discarded as the group MAJdrainage[4&5&3-6&1] is more significant. However it must be noted that interpreting the strength of any variables beyond the top five is not reliable due to their significance level.

Table 9 shows the degree of correlation among the independents. This is done to address the issue of possible collinearity. It can be seen that the soil moisture variable shows high correlation with mean AWHC and mean precipitation as well as the other soil specific parameters. Precipitation also shows high correlation with mean AWHC. As discussed earlier, precipitation is also a fundamental input to the computation of the drought indices and therefore the forward stepwise regression model was rerun without precipitation as an input with the results summarized in Table 5 and Table 6. This model explains 69.16% of the variance in the relationship between the VCI and PDSI. After elimination of the highly collinear precipitation variable, the average soil moisture emerges as the most significant variable while the percentage irrigation and mean permeability decrease in significance.

Table 9 Multivariate correlation model among the dependents

	PercentageIrrigated	MAJ_hydgrp	MAJORITY_LULC	MINORITY_LULC	MAJdrainage	MEANperm	MAJORITYhydr	MEAN_watertab	MEANAWHC	meanprecip	avgsoilmoistr
PercentageIrrigated	1.000	-0.110	-0.284	-0.012	-0.187	-0.046	-0.088	0.119	0.193	-0.244	0.241
MAJ_hydgrp	-0.110	1.000	-0.236	-0.042	0.276	-0.508	0.938	-0.121	-0.033	0.168	-0.022
MAJORITY_LULC	-0.284	-0.236	1.000	-0.029	-0.084	0.312	-0.281	-0.120	-0.231	0.106	-0.164
MINORITY_LULC	-0.012	-0.042	-0.029	1.000	0.109	0.046	-0.054	-0.195	0.113	0.092	0.091
MAJdrainage	-0.187	0.276	-0.084	0.109	1.000	-0.068	0.246	-0.690	0.430	0.512	0.397
MEANperm	-0.046	-0.508	0.312	0.046	-0.068	1.000	-0.512	-0.064	-0.114	-0.084	-0.048
MAJORITYhydr	-0.088	0.938	-0.281	-0.054	0.246	-0.512	1.000	-0.080	-0.044	0.143	-0.036
MEAN_watertab	0.119	-0.121	-0.120	-0.195	-0.690	-0.064	-0.080	1.000	-0.643	-0.720	-0.634
MEANAWHC	0.193	-0.033	-0.231	0.113	0.430	-0.114	-0.044	-0.643	1.000	0.585	0.910
meanprecip	-0.244	0.168	0.106	0.092	0.512	-0.084	0.143	-0.720	0.585	1.000	0.667
avgsoilmoistr	0.241	-0.022	-0.164	0.091	0.397	-0.048	-0.036	-0.634	0.910	0.667	1.000

Model 3 with the modified LULC variable was found to explain 61.43% of the variance in the relationship between VCI and the PDSI (Table 2). The variable representing percent of the county that is forest land was found to be negatively correlated (Table 7). Vegetation with deep roots is able to tap into groundwater thus mitigating the influence of drought in counties with high percentage of forestland. The variable representing percent of the county that is rangeland was found to be positively correlated (Table 7). This is understandable as rangeland is not supported by any irrigation and is completely dependent on precipitation for nourishment. The variable representing percent of the county that is urban land was found to be negatively correlated (Table 7). This is understandable as vegetation in urban areas is watered regularly and protected from drought effects. The variable representing percent of the county that is agricultural land was found to be negatively correlated (Table 7). Agricultural vegetation is also supported by irrigation and groundwater and hence the effect of drought is mitigated. However these two percentage LULC variables have very low statistical significance in the model and can be neglected.

These results show that the effect of drought on vegetation is greatly dependent on the spatial distribution of land-covertypes as shown in the (Vicente-Serrano 2007) studies. Table 9 shows that next to precipitation the soil moisture variable is highly correlated with all other variables and also is the most significant variable obtained in Model 2.

6. CONCLUSIONS

6.1 Summary

The analysis of the model performance statistics for the various drought indices suggests that the VCI is most similar to the 6-month SPI and the PDSI. Both of these drought indices account for antecedent moisture conditions (at least the last 6 months of precipitation). The Z-index, although it is a good measure of agricultural drought, is not strongly correlated with VCI because it does not incorporate antecedent weather conditions.

It was also demonstrated that the relationship between the VCI and the drought indices varies spatially over Texas. Investigation into the variables affecting this spatial variability reveal that soil moisture, landuse category, depth of the water table and soil properties like permeability, AWHC and drainage are useful for explaining much of the spatial variability in the relationship between the VCI and traditional drought indices. Influence of pests and plant diseases are assumed to be absent. In seeking to replace traditional station-based indices with the VCI for monitoring drought, data on these additional variables should be incorporated. Additionally, since this study is from a remote sensing definition of drought, the degree of correlation among the traditional drought indices and the VCI is limited to the degree of coincidence between remote sensing drought and the other kinds of drought (hydrological/meteorological and agricultural drought respectively) that they each measure.

6.2 Further Study

Studying the temporal signals at a higher temporal resolution will reveal a more exact value of the vegetation response lag. Influence of pests and plant diseases also need to be incorporated. In incorporating the soil properties' variables in this study, approximations were made assuming the dominant soil group in the county was representative of the entire county. Also, the spatial distribution of many of the soil sub-components was unknown. Incorporating a more comprehensive soil database in our model will make this study more precise. In investigating the spatial pattern observed in stage 1 of our results, we incorporated variables like percentage irrigation, mean soil moisture and mean annual precipitation which were temporally lumped. A regression model that can incorporate both the temporal and spatial signal of the variables would make a good task for further study. In order to address the issue of the vegetation response lag, the NDVI may be substituted with the NDWI. In order to rule out the influence of pests and plant diseases as well as crop damage due to excessive rainfall, cross referencing of the VCI with thermal indices also may be necessary.

APPENDIX

Table 10 Description of variables in multivariate correlation model

Variable Name	Description	Category Code	Category description
PercentageIrrigated	Percentage of the county under irrigation		
MAJ_hydgrp	Hydrologic group of the majority soil in the county. These codes are an ordinal ranking of the soils' drainage capacity.	1	Sandy, free draining soils
		2	Intermediate drainage capacity
		3	Intermediate drainage capacity
		4	Clayey, free draining soils
MAJORITY_LULC	The dominant Landuse/landcover type in the county	1	Urban Land
		2	Agricultural Land
		3	Rangeland
		4	Forest Land
		5	Water
		6	Wetland
		7	Barren Land
		8	Tundra
		9	Perennial Snow/Ice
MINORITY_LULC	The minority Landuse/landcover type in the county	1	Urban Land
		2	Agricultural Land
		3	Rangeland
		4	Forest Land
		5	Water
		6	Wetland
		7	Barren Land
MAJdrainage	Drainage type of the majority soil in the county. These codes identify the natural drainage condition of the soil and refer to the frequency and duration of periods when the soil is free of saturation.	1	Well Drained
		2	N/A
		3	Moderately Well drained
		4	Poorly Drained
		5	Somewhat Poorly Drained
		6	Somewhat Excessively Drained
		7	Excessively Drained
MEANperm	Average permeability rate (mm/hr) of the dominant soil		

	component in the county.		
MEAN_watertab	Average depth of the water table in the county		
MEANAWHC	Average Available Water Holding Capacity of the soil in the county.		
meanprecip	Average precipitation in the county.		
Avgsoilmoistr	Average soil moisture level in the county.		

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